

Technical Report: The Business Case for Healthcare Information Technology in Nursing Homes

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Summary

We investigate whether the implementation of electronic medical records is associated with higher levels of economic performance in nursing homes in terms of quality, profitability, cost, productivity, and efficiency. Our analysis is based on a survey of Healthcare Information Technology (HIT) usage for approximately 200 New York State Nursing Homes, including 26 that participated in the NY Nursing Home Demonstration project. The survey data are combined with regulatory data from CMS Nursing Home Compare and the NY State RHCF-4 financial reports. The analysis uses a “difference in differences approach” comparing changes in economic performance in a facility before and after HIT implementation to changes over the same time periods in other facilities that are known to not have implemented HIT. The original goal was to focus on the effect of HIT implementation in the Demonstration Project homes. However, since it is likely that there are too few homes in the demonstration project to obtain statistically significant results, most analyses are based on the full sample of 200 homes. We generally find similar results when the sample is restricted to Demonstration Project homes and non-adopters, although the reduced sample size leads many of these analyses to not be statistically significant.

Generally, models considering simple changes in measures of quality or profitability show a weak, often positive, effect of HIT, but this effect is generally not statistically significant in either the full sample or the demonstration project subsample. These analyses provide some evidence of higher quality, and increased proportion of private pay patients, but perhaps slightly lower operating margins. Estimates of multifactor productivity using economic production functions are generally inconclusive on the effect of EMR adoption, and estimates using cost functions are either inconclusive or suggest that HIT implementation alone is associated with slightly higher costs (on the order of 1-3% of variable costs). Estimates of efficiency scores using Data Envelopment Analysis (DEA) suggest that HIT adoption is associated with a 2-3% greater efficiency. The use of difference-in-differences matching estimators that isolate the effect of HIT against comparable non-adopting homes suggests that HIT has a positive effect on quality and gross margins, but this effect only appears after a four year lag.

We also consider whether the benefits of EMR implementation vary by organizational characteristics, specifically the use of progressive work practices that have been found to be complementary to IT investment in the past. Progressive work practices are defined as a combination of greater staff autonomy, greater information sharing, and emphasis on training and cooperative labor-management relations. We find that there is a very consistent positive benefit of HIT in homes that implement or utilize progressive work practices (which include greater staff autonomy, cooperative labor-management relations, and greater teamwork). Facilities that are one standard deviation higher on our measure of progressive practices experience a 2-3% gain in productivity, a 2-3% reduction in costs and a 1-2% incremental efficiency gain upon implementation of HIT (above any direct effect). Thus, there is

evidence of a significant improvement in economic performance associated with HIT implementation when implemented in a suitable organizational environment.

Introduction¹

The productivity of nursing homes is of considerable importance given the ever increasing demands medical care is placing on Federal and State budgets, and the aging of the US population which is expected to considerably increase the demand for nursing home services. New York State alone has over 111,000 residents in nursing homes, and the state spent nearly \$21Bn in Medicaid disbursements on long term care in 2008.²

Healthcare information technology (HIT) has the potential to improve the efficiency of nursing home care. In the broader healthcare sector, HIT has been linked to reduced cost, reduced medical errors, and improved quality of patient care, although most of the evidence of substantial positive impact is based on individual case studies. Nonetheless, the few large sample statistical studies also tend to show modest, positive benefits of HIT investments (see a brief review in Beard, Elo, Hitt & Housman, 2010). It is believed that these same benefits could apply to nursing homes. In particular, HIT systems that enable the capture, processing and retrieval of resident medical records (electronic medical records systems or EMR) are believed to enable nursing homes to better standardize and manage the care process, improve the quality of documentation of resident care, and free up the time spent by direct care staff on documentation and coordination to provide more substantive resident contact, potentially improving resident quality of life. Automation of the medication process is believed to reduce medication costs through the elimination of waste and duplication, decreased medication errors, or by providing decision support to allow physicians to make better medication choices (fewer and/or lower cost).³ Other aspects of HIT systems in nursing homes enable off-site workers (such as doctors or RNs working off shift) to obtain necessary information to better support care. Finally, more accurate data capture on residents' health conditions and treatment may facilitate improved billing for services yielding greater revenue. Collectively, there are a number of pathways through which HIT in nursing homes can potentially improve the quality of care, decrease costs, increase profitability, and increase the effectiveness of nursing home staff.

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² See "Long Term Care Financing in New York," The Empire Center for New York State Policy (March 3, 2011) (<http://www.empirecenter.org/Special-Reports/2011/03/ltc030311.cfm>) (downloaded 6/8/11)

³ For a vendor's perspective on the benefits of HIT, see "Electronic Medical Records in Long Term Care," presentation by SigmaCare/eHealthSolutions at the American Health Care Association Conference (AHCA) October, 2007.

In 2007, New York State embarked on a \$13.5 million “demonstration project” (DP) grant to implement electronic medical records in approximately 21 nursing homes, selected through a competitive process to be representative of nursing homes in the NY metropolitan area. The project provided a subsidy for implementation costs and 18 months of operating costs for the SigmaCare System provided by eHealthSolutions, the vendor selected through a separate process managed by the Quality Care Oversight Committee (QCOC) which was charged with managing the grant. This SigmaCare system provided electronic medical records (EMR), workflow monitoring and management, and data access on a variety of devices on- or off-site including PCs, handhelds, and tablets.⁴ The system also had the capability to support medication administration or integrate with other off-site systems such as hospitals, laboratories or pharmacies. Essentially all demonstration project homes adopted the EMR capabilities, and many adopted the more advanced capabilities. We will therefore refer to this particular HIT implementation as an EMR implementation since that is typically the first HIT capability adopted. The first DP implementation was initiated in 2007 and most were completed by the end of 2008.

A condition of participation in the demonstration project was that the homes had to allow a study of the impact of the system on resident and nursing home staff. This study was the product of a later initiative, funded by the Commonwealth Fund,⁵ to study the “business case” for EMR implementation. Although this study was supported by the QCOC and coordinated with the other DP studies, participation in the business case analysis was voluntary. The study was focused on two questions: 1) Does the implementation of EMR create sufficient private benefits to nursing home operators so that private adoption is profitable? 2) Does the implementation of EMR create sufficient overall financial benefits such that its adoption should be encouraged by regulators, governments or other third-party payors?

This analysis is done at the nursing home level, rather than a unit or activity within a nursing home, because these are the measures observable to regulators and other outside parties, and also the way nursing homes have historically been evaluated in studies of quality, efficiency or cost in the prior literature (both academic and practitioner). While the focus is on the performance of the demonstration project (DP) homes, it was recognized that the DP sample was likely too small to show conclusive effects on the impact of the technology at the nursing home level, especially since there has been limited time since the implementation.⁶ In addition, even for analyses restricted to the DP, a larger control group (homes that are known to not have adopted EMR) would prove useful. Therefore, a key part of this study is a survey, conducted in late 2009, on EMR implementation, use, and associated organizational practices of privately operated, NY State Nursing homes with at least 60 beds (a population of approximately 400 homes). This analysis is based on the results from the 198 homes that provided usable responses to the survey, plus information from a supplemental survey conducted on the DP homes (an additional 10 responses), and other data from the DP for all DP participants. Most

⁴ See <http://www.sigmacare.com/> for further details on the SigmaCare system.

⁵ The Commonwealth Fund is a private foundation devoted toward improving performance in healthcare (<http://www.commonwealthfund.org/>). This project was funded through the “Frail Elders” program.

⁶ A number of studies on the productivity or organizational impact of information technology suggest a lag of 1-3 years between implementation and full benefits are realized (see e.g. Brnyjolfsson and Hitt, 2003). At present, we are still within that window for most homes we are able to observe.

analyses reported either compare the DP homes to a control group of known non-HIT adopters (about 100 homes in the survey), or compare all adopters (DP or not) to non-adopters.

Four types of models were estimated to examine our research questions. First, we begin with simple analyses of performance (e.g. gross margin, quality scores), or operating measures (average reimbursement rates, resident mix by payor) to examine changes experienced by the nursing homes following EMR adoption. These measures, or similar ones, are commonly used to track nursing home performance internally and externally. Performance effects of EMR were also estimated by three types of economic models of productivity: production functions, cost functions, and efficiency analysis (using Data Envelopment Analysis or “DEA”). Each of these approaches has precedent for the study of the economic impact of information technology, or the economics of nursing homes, with cost function and efficiency approaches being the most common in the healthcare performance literature and production functions being the dominant approach for the study of the economic impact of information technology more broadly.

Overall, we generally find mixed results as to whether implementation of HIT increases performance in the population of homes that adopted HIT. In general, estimates of performance ratios and productivity suggest small, but generally not significant benefits in productivity and quality, and a small, clear shift from Medicare to private pay residents (at least in the full sample). Cost estimates are either neutral or suggest that the implementation of EMR increases costs by approximately 2.5%. However, we find the opposite result for efficiency analyses, with EMR implementation moving homes about 2.5% closer in cost per unit of output to the most efficient comparable home.

However, perhaps more interestingly, we consistently find that the performance benefits of EMR are influenced by organizational practices at the homes that adopt the system. In particular, we find consistent evidence that facilities with progressive work practices (a system of practices that include management-labor cooperation, greater worker autonomy in decision-making, and an emphasis on team work and information sharing) consistently improve performance. Homes that are one standard deviation higher on our measure of progressive work practices have consistently higher performance by 1% to 3% or more in our economic models (the performance ratio models do not have enough statistical power to provide usable results on this issue). These results are above the direct effects of EMR implementation in all homes and any pre-existing differences in performance between homes that adopted EMR and those that do not. The best results are found for the full sample, and are sometimes, but not always corroborated by the smaller sample of demonstration project homes. This is perhaps not surprising given that the theoretically expected and empirically observed effect sizes are relatively small compared to ordinary variation in nursing home performance. Therefore, larger samples are critical in identifying the effect.

Our results are also consistent with prior work in HIT which find results on the same order of magnitude, and studies in IT management that suggest the importance of specific complementary organizational investments in determining the value of IT investment. When compared to the original cost of the demonstration project (about \$2,000 per bed-year) breakeven over this period would require about a 2% decrease in cost which appears to hold at least for the homes with progressive work practices.

However, this threshold is likely high because the demonstration project involved mostly up front initial costs (ongoing operating costs are substantially lower) and some demonstration project costs were associated with research and administration of the grant. The high variance of the estimates and mixed results (in particular increases in cost following EMR) make it difficult to make strong recommendations for the general EMR investment or to specifically examine whether the demonstration project homes receive benefits (or experienced costs) that were different than the broader population. These issues will be further discussed in the conclusion.

Prior Literature and Modeling Approaches

There is an extensive literature on the economic performance of nursing homes and a substantial literature on healthcare IT in other settings, but there are essentially no large sample studies on the impact of electronic medical records on long term care. This work also relates to the literature on IT and organizational complements, although to our knowledge these complementarities have never been studied in the healthcare IT context.

Previous work on nursing home performance has considered the determinants of nursing home quality or cost with special emphasis on market characteristics such as competition (Gertler and Waldman, 1992; Grabowski and Hirth, 2003), organizational variables such as for-profit status (e.g., Arling, Nordquist and Capitman, 1987; Nyman and Bricker, 1989; Fazel and Nunnikoven, 1992; Spector, Selden and Cohen, 1998; Choi, 2002) or chain membership (e.g., Fazel and Nunnikove, 1993; Banazak-Holl, Berta, Bowman, Bam and W. Mitchell, 2002), and policy variables such as a shift to prospective payment systems (Sexton, Leiken and Sleeper, 1989). In general, competition, for-profit status and chain membership are all associated with greater productivity or efficiency. However, none of these studies have addressed the use of electronic medical records or any type of HIT in long term care.

These studies use a variety of methods, with a few studies estimating economic cost functions which are the most developed theoretically (Arling, Nordquist and Capitman, 1987; Gertler and Waldman, 1992; Mukamel and Spector, 2000). Cost functions represent an economic relationship between total or variable costs of a facility, the prices of its inputs, and the total quantity of outputs. Generally, the form of the cost function is assumed from a family of flexible functional forms (usually the transcendental logarithmic function), and then economic theory is utilized to derive implications of this cost function such as the demand for variable inputs like labor and materials, or to place restrictions on the cost function parameters (see Berndt, 1992 for the general practice of cost function estimation). Cost functions are widely used in settings where there are multiple outputs, or where the firm objective can be characterized by cost minimization subject to some (nearly) fixed level of output. Both conditions appear to characterize the nursing home industry. With capacity utilization 90% or more at most facilities coupled with regulatory restrictions on capital investment, output quantity is largely fixed. Most homes attempt to increase profits by lowering cost or competing for higher reimbursement residents (private pay and Medicare). To study the influence of a firm characteristic or policy change, additional variables are entered additively into the cost function or factor demand equations – the interpretation being that the coefficient on these variables potentially measures the marginal effect of

the measure on cost or factor usage (more productive firms have lower costs or make greater use of lower cost factors).

A larger proportion of prior work relies on Data Envelopment Analysis (DEA) based frontier methods (e.g. Nyman and Bricker, 1989 for an example). Data envelopment analysis is an optimization-based method that uses a linear programming model to identify facilities on an “efficient frontier”. The efficient frontier represents the combinations of outputs and inputs such that no firm can produce more output than an efficient firm without using more inputs. The advantage of this approach is that it imposes no structure on what makes for an efficient facility except to “do more with less”. However, a consequence of this feature is that depending on the choice of outputs and inputs, some substantial number of facilities are deemed fully efficient because other facilities are not directly comparable. There is also no allowance for error in the construction of efficient frontiers so random variation can lead incorrect facilities to be deemed efficient. Consequently, the effectiveness of these methods depends critically on the cleanliness of the data and careful selection of inputs and outputs. Prior work in nursing homes generally treats inputs as labor of different types (nurses, CNAs, management, etc.) and outputs as resident days of various types and some measure of quality. Once the efficient frontier is constructed, all other firms are compared by their distance to the frontier. Distance can be interpreted as the percentage decrease in input use needed to achieve the same level of output as a facility on the efficient frontier, and therefore, it has the same interpretation as other productivity measurement methods.

A few studies utilized a technique called Stochastic Production Frontiers (Vitaliano and Toren, 1994) which are a hybrid of cost functions and DEA, but tend to yield similar results to pure cost function estimation. Some studies, especially those that focus on quality rather than performance use specially developed models where some outcome variable is regressed on the variables of interest (see e.g., Grabowski and Hirth, 2003).

There is an emerging literature on HIT in hospitals that rely on similar methods (typically cost functions, some DEA) that have linked use of various HIT systems to performance. While much of the earlier work is in the form of case studies and anecdotes (see e.g. GAO, 2003 for a summary), a few studies have emerged that estimate the impact of HIT on outcomes using large sample data and more structured economic models (Borzekowski, 2003; Hausman, Hitt, Elo and Beard, 2009; Atkinson and Cockerill, 2006 for cost function studies; Menon, Lee and Eldenberg, 2000 use DEA). In general, these studies find modest but significant effects of health IT, especially at higher levels of investment. Firms at the leading edge of HIT investment may have productivity on the order of 1-3% greater than other firms that have made less substantial HIT investments. In contrast to nursing homes, however, most hospitals have at least some investments in organizational IT systems, whereas many nursing homes have minimal IT except for personal productivity applications. Thus, IT in nursing homes may be better captured by the adoption decision rather than the level of use or investment quantity which would be more appropriate for hospitals.

This work also draws on the general literature on the productivity of IT investments. In particular, this literature stresses the importance of complementary organizational investments (such as human capital,

organizational investments, or restructuring) in realizing the value of IT (see Melville & Kraemer, 2003 for a survey). A relevant finding of this literature is that firms that utilize a specific set of organizational practices, specifically decentralized decision making, higher screening for and development of human capital, and group based incentive schemes tend to receive greater benefits for each dollar of IT investment (Brynjolfsson and Hitt, 2002). A parallel measure was developed for this study based on this research and the work by the demonstration project labor force team that captures decentralized authority, training, information sharing, and cooperative labor management practices. A reduced version of this measure, emphasizing the constructs that had the greatest predictive power from a larger set of questions, was included in our EMR implementation survey.

Most prior IT value studies utilize a production function framework where output is regressed on some combination of inputs. This approach is perhaps easier to interpret than cost functions or efficiency scores, but has the drawback that it can only handle a single type of output at a time so we are limited to examining overall revenue as the primary output.

Finally, this study also examines results from a difference-in-differences matching estimator. This type of matching estimator is commonly used when the research design includes observations from before and after a significant change, such as EMR adoption. Matching estimators have the advantage that they do not require specification of a functional form, and have been widely used in the literature on non-experimental policy evaluation.

More discussion of the technical aspects of production function, cost function, DEA estimation and matching estimators appear when the models and results as well as a discussion of implementing these models in a “difference in difference” style setting which compares adopters to non-adopters of EMR controlling for pre-existing difference in facility characteristics between the two populations.

Data

EMR Adoption Survey. The primary unique data source for this analysis is a survey conducted in late 2009 (completed in early 2010) of HIT use and work practices in NY State Nursing Homes. From an initial population of approximately 600 homes we removed homes that were Government operated, those that had less than 60 total nursing home beds, and those participating in the demonstration project. Potential contacts were identified through the homes regulatory filings (RHCF-4) that identified owners or administrators. These individuals were contacted by telephone and were interviewed directly if they were sufficiently familiar with nursing home operations. If not, we obtained a referral where possible to an informed respondent. The survey was conducted by the Cornell University Survey Research Institute (SRI), and was pretested on demonstration project homes before being deployed in the field. This approach yielded 198 completed surveys out of an initial population of approximately 400 homes for a response rate close to 50%. We also conducted the same survey for the homes in the demonstration project, although some questions were removed since the answers were known (e.g. date of HIT implementation, vendor). Somewhat surprisingly, we received no greater response from the demonstration project homes – interviews were only successfully completed with 10 out of the 21 total homes that had HIT implementations as part of the demonstration project. Consequently, many of the

analyses of demonstration project homes have to rely on demonstration project rather than survey data.

The survey was approximately 20 minutes long and focused on the date of HIT implementation, the features used (electronic medical records, medication administration, remote access), and the extent of use by staff. In addition, questions to support two measurement scales were included. The first, on progressive work practices, was developed based on questions used by another study team examining labor force issues in the demonstration project and similar to prior work on IT and organizational complements. The scale included 7 questions which had proven most helpful in discriminating homes in a prior analysis (Avgar and Lipsky, 2011. 2010) and addressed information sharing, teamwork, worker autonomy, training and labor-management cooperation (see Appendix for full questionnaire). This scale showed good reliability with a Cronbach's alpha of 0.71 (this scale is referred to as the *Progressive* work practice scale – for the remainder of the document, variable names will be indicated in italics). We also included a battery of 11 questions to measure inhibitors of information technology implementations based on prior work on IT investment generally (Tambe, Hitt, and Brynjolfsson, forthcoming). The components of this scale are used as instruments to predict healthcare IT adoption to control for potential reverse causality between performance and HIT in the broader sample. Since the DP homes were selected without regard to performance, the adoption of EMR in these homes can be reasonably considered exogenous, so this instrument is principally for homes not in the DP. The Cronbach's alpha of this scale as 0.73, but we generally use the individual components of the scale rather than the scale composite in most analyses since this is more statistically efficient and we are not interested in measuring the marginal effect of the inhibitor measures.

Other than the two organizational scales described previously, the critical question in the survey was the date of EMR adoption (if any). Since EMR is generally the first HIT technology adopted, this represented the first HIT adoption date. We also examined the effect of other technologies (medication administration, remote access, external provider integration) but the sample was not sufficient to obtain reliable results for these constructs separately from overall adoption. Therefore, this report focuses specifically on EMR implementation. For homes in the DP that did not respond to the survey, we obtained the date of implementation from the vendor. In our survey, 49.8% of facilities had adopted EMR by the end of 2009, with the earliest adoption date being 2005. When the additional demonstration project and control homes were added that were present at the time of our analysis, we had EMR adoption data for 219 homes with 53% being adopters. However, most estimates are done using a subsample of 203 homes that have complete financial and quality data.

Financial Data. The primary source of financial and operating data is the NY State Residential Health Care Facilities Cost Reports (RHCF-4). These data, and their comparable data from other states, are generated by the Medicaid rate setting process and have been extensively used in prior research. We have annual data from 2003 to 2009, although we only use the 2004-2009 data for our estimates (the 2004 cutoff was chosen as 1 year prior to the earliest adoption date). These data are highly detailed and include measures of revenues, resident mix (resident days and revenues by payor – Medicaid, Medicare,

Private), staffing by role,⁷ for-profit status, location, presence of a union, costs (labor, materials, purchased services), bed size, and services provided. These data also include extensive capital accounting information, but this was not utilized because most of the meaningful variation in capital is due to facility size which is reasonably captured as number of available beds. Moreover, since capital investment is regulated by “certificate of need” regulations that limit the ability of homes to make changes in capacity, most of the variation in capital measures is due to financing rather than actual variation in productive capital (see a related argument in Nyman and Bricker, 1989 or Gertler and Waldman, 1992).

Generally, the values on the RHCF-4 data were taken directly, although there is a small percentage of coding error present in the data which is clearly apparent when the data are observed over time for the same home. These were corrected where possible (e.g. incorrect home identifiers, missing bed size). Expense and staffing data at the top and bottom 1% of the sample were screened, and in some cases eliminated because these were inconsistent with other data. All removal of anomalous data was done on individual variables – a home is still included in the sample if there is missing or removed data on one measure or in one year but not others. However, we do try to keep consistent samples between the productivity and cost function analyses so missing data on some constructs may remove that home observation from all analyses, even if that analysis does not rely on a particular variable.

Quality Measures. Nursing homes are subject to annual inspections in which the facility and resident condition are evaluated by Government inspectors. A summary of results of the annual inspection (“survey”) are made publicly available at a facility level by the Center for Medicaid and Medicare Studies (CMS) Nursing Home Compare Database. Nursing Home Compare (NHC) is based on two other sources: the CMS Online Survey, Certification and Reporting (OSCAR) database and the CMS Nursing Home Minimum Data Set (MDS) database. Since the source data are not publicly available and our analysis is at the facility level rather than the individual resident, we rely solely on the data produced in Nursing Home Compare. NHC is updated quarterly although the underlying data only change when the survey is conducted, which is typically annual (more frequent for homes with known problems). The Nursing Home Compare data contains three types of data: quality measures (QM) which are a summary of individual resident health condition (18 measures total) and is derived from the MDS, complaints received (individually listed, categorized by severity), and deficiencies identified by the survey team (individually listed, also categorized by severity) which are derived from OSCAR data. The Complaints and Deficiencies remain recorded on the database until resolved and appear a minimum of one quarter. The QM indicators are based on running averages of residents that most recently were examined by a survey and reported in MDS, aggregated to the home level.

We experimented with a number of methods for incorporating the quality data, including directly using the individual raw data for analyses. Prior work has used a variety of methods including restricting the analysis to specific measures (e.g. quality as proxied by the incidence of Bedsores or Urinary Tract infections) or scales constructed from the data. We adopted the scale construction approach since it

⁷ The staff data is divided by Registered Nurses (RNs), Licensed Practical Nurses (LPNs), Certified Nurses Aids (CNAs), administrators and managers, other medical staff, and clerical and administrative staff.

more readily integrates with the performance measures used, and analyses using the individual quality measures were largely inconclusive. The approach for constructing the scales parallels the methodology CMS uses for overall evaluation of nursing homes in their “star rating” system.⁸ CMS constructs numerical scores for health quality (from the quality indicators), complaints and deficiencies, which are then combined to create an overall score. CMS then assigns star ratings (one to five stars) based on quintiles of the composite scale. We utilize a similar methodology for constructing the individual quantitative scales following the CMS method, but keep the raw scale score for each. Specifically, we constructed a separate scale measuring health quality (*QualityScore*), complaints (*ComplaintScore*) and deficiencies (*DeficienciesScore*).

The complaints and deficiencies scales are relatively simple to construct. Each deficiency or complaint is assigned a “severity” rating on a 12-level scale (A-L) which captures the actual severity and the number of residents affected – a low severity item (A) is “isolated, no actual harm with potential for minimal harm” and a more severe item (L) is “widespread, immediate jeopardy to resident health or safety”. There is also an adjustment for the most severe issues that affect resident quality of care. The point values range from 0 for minor issues (severity A, B or C), to 175 per deficiency/complaint for the most severe issue related to resident safety. CMS also incorporates an additional adjustment (penalty) for the longer an issue takes to resolve which we do not do since we are using the full time series of the data. Persistent problems are already accounted for by the variation in the score over time. Technically, the scale is unbounded since the inspections can identify an unlimited number of deficiencies and individuals can make an unlimited number of complaints, but in our data we found that they ranged from 0 to 437 for complaints and 0 to 572 for deficiencies. The mean of the Complaints scale was 11 and the mean of the Deficiencies scale was about 20, with a variance of both measures of about 50. Thus, most homes have only a few minor issues if any, but a few have recurrent severe issues.

The quality measures are constructed using a more complex method also following the approach used by CMS. First, each of 10 critical quality indicators are broken into quintiles based on population values of the measure across homes in the sample. CMS uses national averages, while we chose the averages for NY State only in each year. Point values are then assigned for each quintile. The highest (best) quintile gets up to 20 points for each of two measures related to activities of daily living (change in ambulatory status, change in assistance required for activities of daily living), and up to 12 points for each of the eight other measures. The scale is linear in the quintile with the lowest quintiles earning zero points. The overall quality score is the sum of the individual scores for each quality measure. Theoretically the scale can range from 0 to 148, but in our sample this score ranges from 37 to 130 in 2009, with a mean of 74.7. For all three scales, we average the three preceding quarters to get an annual scale to take into account different timing of the survey which would generate an update to the figures. Note that a higher score on the Quality measure is better, while lower scores for Complaints and Deficiencies are better.

⁸ See details of the methodology in “Design for Nursing Home Compare Five-Star Quality Ranking System: Technical Users Guide,” Center for Medicare and Medicaid Studies (March, 2010).

The principal measures utilized in the study are summarized in Table 1, and details on the individual measures are included in the Appendix along with the full EMR adoption survey. The final dataset includes data on as many as 219 homes from 2004 to 2009, although the typical cross sectional unit (year) contains approximately 203 homes.

Analysis: Before and After Comparisons Framework

To examine whether the implementation of EMR systems had a substantial effect on nursing home operations we conducted a “difference in difference” analysis of whether operating or performance measures changed more in homes that implemented EMR than those that did not, controlling for possible differences in the population of eventual adopters from the population of non-adopters. The general form of the estimating equation is for each home (h) in each year (t):

$$PerformanceMeasure_{h,t} = \alpha_0 + \beta_{EMR} UseEMR_h + \beta_{AfterEMR} AfterEMR_{h,t} + year(t) + other\ controls + \varepsilon_{h,t}$$

The variable *UseEMR* takes the value 1 if the home ever uses EMR and zero otherwise. This variable controls for pre-existing differences between implementors and non-implementors of EMR. The variable *AfterEMR* takes the value 1 for the year EMR is implemented and all subsequent years, and zero otherwise. This is the primary variable of interest, because it has an interpretation as the marginal effect of EMR implementation in this framework. Whether this can be interpreted as causal depends on whether it is believed there are common factors that coincide with EMR implementation time and affects performance for only the period after implementation. This approach is robust to the possibility that homes that adopt EMR may differ in performance levels generally. Thus, when this variable is significantly different from zero, it is plausible that the adoption of EMR had a causal effect on the performance measure. We experimented with considering time since adoption or defining post-adoption as the year following adoption; neither appeared to yield improvements in the analysis. This is likely due to the relatively small number of post-adoption observations (about 2.5 on average).

All regressions here and in subsequent models (unless otherwise noted) use this difference in difference approach and include controls for year to account for shifts in the performance measure due to external economic conditions. For the operating performance measures, three separate analyses were run with different levels of additional control variables: no additional controls, a set of firm level controls (Quality, Number of Services Offered, Resident Composition, Bed Size, Unionization, For-Profit status, presence in the NY metropolitan area), and a fixed effects analysis which controls for all time invariant characteristics of the individual homes. For most other analyses, we use the full control set in all reported analyses. These variables are used throughout, so we discuss the motivation for their inclusion here.

We include quality measures since it is plausible that higher quality has an influence on cost or other performance measures (although it is an open debate in the operations literature as to whether improved quality leads to higher costs due to additional effort, or lower costs due to the reduced need for remediation). We include the three indices for Quality computed from Nursing Home Compare (*QualityScore*, *DeficiencyScore*, *ComplaintScore*). Almost all prior work in nursing home performance contains some control for quality.

The RHCF-4 survey lists 20 services that can be performed in nursing homes or contracted out so we control for the number of services performed (*Services*). More services are likely to be associated with greater revenue and greater cost, with the cost effect potentially larger due to a greater complexity of management. The typical home in the sample performs 11 of the 20 services listed on RHCF.

We control for resident composition because it directly influences revenue through payment, and may indirectly represent other aspects of the home since nursing homes aggressively compete for private pay residents but not Medicaid residents. The resident composition variables are *PctMedicare*, *PctMedicaid* and *PctPrivate*. We drop *PctPrivate* since that is entirely determined by the other two given that the three measures together sum to 100%. In our sample about 15% of residents are private pay, and 74% are Medicaid as measured by resident days. Most prior studies included controls for resident composition.

Prior research has shown that for profit facilities are more productive than not for profit facilities, so we include a binary variable *ForProfit* representing for-profit status. About half of all facilities in our survey and nearly all the demonstration project homes are for-profit. This variable appears on essentially all prior nursing home studies and study of this specific variable has been the focus of much of the prior literature.

We include a control for presence in the NY Metro area (*NYMetro*) since prior work has controlled for location and found that being in an urban location has an influence on cost and reimbursement. This control is also useful in interpreting the measure of the presence of a union (*Unionization*) since urban homes tend to be more unionized. Prior work is mixed on the typical signs of these variables. About 60% of the full sample is unionized and 30% are in the NY metropolitan area.

We use the logarithm of Bed Size (*logCapacity*) as a control for scale. This variable also serves as a proxy for capital stock in the later analyses. Generally, we expect (and indeed find) increasing returns to scale, so this variable will often be positively associated with performance. The average facility bed size is 178 in our full sample and 212 in the demonstration project (in geometric means).

Finally, we utilize an index of competition proposed by Gertler and Waldman (2002)⁹ which is based on the insight that nursing homes aggressively compete for private pay residents but that this degree of competition depends on the number of other homes in the same geographic region (in our case, County). For each county, we compute the share each home has of private pay residents (from RHCF) and then compute a Herfindahl index as the sum of squared market shares. The index ranges from 0 to 1, with 1 representing a monopoly over a geographic region and 0 representing an infinite number of facilities each with very small market share. Overall, most of NY State is competitive, with the concentration index being less than 26% in all counties and the average concentration index over homes being 7% (this is not the average over counties which is substantially higher, but in part reflects the fact

⁹ This measure is the sum of squared market shares within a county for private pay resident. A higher value of this measure indicates less competition since the market is less “concentrated”. Prior work has suggested that competition for private pay residents is a substantial driver of cost and quality (Gertler and Waldman, 1992).

that counties with more homes will have a lower competition index and they will make up more of the sample simply because of the number of nursing homes).

These variables represent the majority of study variables considered in prior research. There are a few deliberate omissions. We do not consider whether the home is part of a chain since multiple home ownership by the same legal entity is discouraged by New York State Law and technically “chains” are not allowed.¹⁰ We do not control for the intermediate care versus skilled care residents since this distinction is not used in New York at the time of our study. Unfortunately, we do not have controls for case mix,¹¹ since these are not available in the RHCF or Nursing Home Compare datasets, but these may be proxied by some combination of the other variables (resident composition and the Quality score). Most of the other constructs that appear in prior research that we did not include are idiosyncratic to the specific datasets or subsumed in our other measures. Thus, we control for most of the known factors that influence nursing home performance. These controls are used throughout the analysis except where a particular control appears in the model directly (e.g. bed size – *logCapacity* -- is a capital proxy in the cost function; *QualityScore* is treated as an output in our DEA analysis so they are omitted in these analyses).¹²

Each analysis is repeated for three samples – the full sample of survey respondents (~203 homes, 53% of which are adopters), the demonstration project homes plus all non-adopters (approximately 115 homes, with 17 adopters), and the demonstration project homes alone (17 homes with complete data). The *UseEMR* variable is dropped in the fixed effects and demonstration project only analyses since this variable is constant across homes and therefore doesn’t vary for the demonstration project or is subsumed in the fixed effect. For the most part, the DP only sample does not generate reliable estimates due to the small sample size, but the estimates are presented nonetheless unless they are completely nonsensical. Since we are using repeated observations of the same facilities over time, we utilize Huber-White Robust (clustered) standard errors to adjust for repeated observations, or utilize panel data methods where these adjustments are automatic (fixed effects, random effects). We also experiment with more advanced panel data methods – GEE which allows for arbitrary correlation between different years in the panel, and panel specific error structures that estimates a cross-time covariance matrix for each facility. These methods generally returned similar results to more standard approaches and so are not emphasized.

Analysis: Simple Operating Ratios

For the operational ratio analysis we considered the following operational and performance measures:

¹⁰ In New York, every nursing home operator must have an owner with a nursing home operator’s license for that home. The State apparently does not issue multiple licenses to the same individual. However, nursing homes can claim costs associated with administrative services from another company allowing for a limited amount of shared services among homes.

¹¹ Case mix is often computed using restricted identifiable data direct from the MDS. We do not have these data for this study.

¹² We thank Sheldon Schechter and members of the Quality Care Oversight Committee (Martin Scheinman, Jay Sackman, and William Pascocello) for assistance in understanding business practices, regulation and financial reporting in NY nursing homes.

- Staffing (Nurses per bed and all FTE per bed).¹³
- Financial: Gross Margins (with and without Administrative costs)¹⁴, Reimbursement Rates
- Quality:¹⁵ Quality Measures, Complaints and Survey Deficiencies
- Resident Composition: Percentage of Medicare, Medicaid, and Private Pay resident days

The staff measures provide some sense of whether labor productivity or staff mix has changed since EMR implementation given that the size and capacity utilization of these facilities are generally stable over time. The three Quality constructs measure the quality of medical care (the QM Score) or operational quality (Complaints, Deficiencies). Gross margins provide some indication of overall cost efficiency or profitability, and rates (Medicare, Medicaid, or private payor) may provide some indication of whether firms are able to capture more revenue from their resident population.¹⁶ Finally, we consider resident composition with the idea that a successful home can attract more private pay patients and therefore increase profitability since private pay residents generally are more profitable than Medicaid residents.

Table 2a summarizes the results of this analysis on the EMR variables.

Staffing. There were no significant changes in staffing before and after in simple comparisons except in the fixed effects analysis which suggests that both Nurses declined by 9% and all FTE Staff declined by about 7% in demonstration project homes relative to the control full control group. These estimates were much larger than any of the other figures, which tended to be negative but nowhere near significant. Moreover, we do not expect staff to change substantially in demonstration project homes due to agreements made to limit staff reductions as part of the project. We are therefore skeptical that they represent anything other than a data anomaly (which is not unusual in fixed effects analyses). Results are not substantively changed when we consider larger or smaller aggregate staffing groups.

Financial. There appears to be a small decrease in gross margin in the demonstration project homes following implementation of as much as 2.7% in gross margin ($p < .1$) in the fixed effects analyses. The direction of the effect is consistently negative for the demonstration project homes. The results for the

¹³ Results of these measures were similar whether we used and additional size control or not, so we report the simple comparisons without size controls for comparability to the other analyses.

¹⁴ One concern about profit measures is that privately owned homes may “take profits” in the form of administrator compensation to owners. Thus, we conduct profit analysis with and without administrator salaries included. There does not appear to be a material difference in the results. Moreover, this issue will have no significant effect on subsequent analyses which are based on staff rather than staff cost, or do not focus on profits.

¹⁵ We also considered using discharge rates (due to death or hospitalization) since these may provide some indication of the ability of the home to maintain health status (although the numbers are heavily confounded by incoming health status of the resident population). None of these analyses were conclusive so they are not reported.

¹⁶ Medicaid and Medicare reimbursement rates (which cover 87% of all residents in the sample) are based on costs and resident health condition. We therefore cannot distinguish higher rates due to having residents with more severe health conditions from the ability of the home to maximize revenue by ensuring that all residents are coded at the highest level they can legally be assigned (this is referred to as “upcoding” and is sometimes argued as a benefit of EMR to nursing homes). Given our data and the results, we cannot make a clear statement as to whether changes in rates are due to upcoding or changes in incoming resident health condition.

full sample are slightly positive but nowhere near significant. This is despite the fact that demonstration project homes were able to increase their Medicaid rates, although these gains only appear for demonstration project homes, and only partially compensates for lower average Medicaid rates for DP homes. The population as a whole of EMR adopters saw their Medicaid average rate drop by approximately \$30 per resident-day, but this effect appears to be driven by changes in the resident population at the home since the effect disappears when additional controls are included.

Quality. There are no conclusive results on deficiencies or complaints. Some fixed effects analyses show a small increase in the deficiency score. However, the effect on the overall *QualityScore* was positive, and significant for the full sample. The typical EMR adopter had an increase of about 3.5 points ($p < .1$) relative to a baseline score of 74 in 2009. This is equivalent to moving up one quintile relative to the population on one of the 10 QMs forming the scale. The sample restricted to the demonstration project homes only was positive but smaller and not significant. Analyses considering the individual quality indicators were largely inconclusive. It is likely that any comparison of quality is confounded by initial resident health condition, especially in the absence of a case mix control variable.

Resident Composition. Firms adopting EMR increase their proportion of private pay patients by about 3.0% ($p < .05$) and decrease their proportion of Medicaid residents by about 2.8% ($p < .05$). The results are directionally consistent but not significant for the demonstration project homes alone. These are substantial changes given that the baseline proportion of private pay residents is about 15% in our sample. However, given that the (geometric) mean of bed size is about 178 in our sample, this implies an increase of only about 5 private pay residents on average in a year. Examining the pattern of results across specifications, this appears to be a real effect and not a statistical artifact.

Other Analyses. The conclusions do not materially change when additional controls are added (location, for-profit status, resident composition, unionization, quality, service breadth, and competition). Homes with greater breadth of services are more labor intensive, for-profit homes are more efficient and unionization has a neutral effect on most measures especially when we control for whether the home is in the New York City metro area. Less competition is associated with higher margins and prices, but otherwise has no effect on operational measures. We also conducted these analyses considering the time since implementation or changing the definition of the implementation date to be 1 year following implementation, but found no conclusive results.

Analysis: Matching Estimators Applied to Performance Ratios

The difference-in-differences matching estimator compares differences in outcomes in EMR adopting homes before and after EMR implementation with differences in outcomes during the equivalent period in homes that did not adopt EMR but are similar across other observable dimensions (Heckman, Ichimura, and Todd 1997). The “before” year for all nursing homes is the year prior to EMR implementation, but in various analyses we allow the “after” year for each home to vary from 1 to 4 years after the EMR implementation year to allow for the possibility of lagged effects.

Table 2b summarizes the results of the analysis when using matching estimators and time lags ranging from 1 to 4 years after implementation. No results are significant one year after implementation, but

the estimates on deficiency scores and gross margins are significant four years after implementation. Moreover, the changes in point estimates in the interim years on these variables are consistent with the hypothesis that the effects of EMR on these outcome variables are growing larger as the time window extends further out from the EMR implementation date. This lagged effect is consistent with other work that has shown that full benefits from IT investment are often realized only after a lag period (Brynjolfsson and Hitt 2003), but the four years required for the lagged effect to appear is somewhat longer than the one to three year window observed in prior work.

Summary of Results on Performance Ratios

For the most part, the homes that implemented EMR had neutral or favorable changes in their operating measures, with possibly the exception of operating margins. However, none of these analysis show large or conclusive results, most of the regressions have relatively low explanatory power, and there is considerable estimation variance even in variables where we have strong prior beliefs as to what their values should be.

One implication of these results is that it would be challenging for an individual home to get a clear indication that an EMR implementation led to significant improvement in overall operating performance by looking at simple ratios of either financial measures of quality indicators. This would suggest careful attention to more micro-level analysis of return on investment (e.g. study specific cost or quality impacts that can be tied directly to a specific aspect of the system) or to other types of more complex analyses such as productivity or efficiency computations which are more sensitive to small changes in operations. Our matching estimator results do suggest a pattern of increasing benefits over time, but the relatively recent adoption of EMR in long term care limits the ability to draw strong inferences about long term benefits.

Analysis: Productivity

Much of the extant literature on the productivity of information technology investments rely on methods in economic production theory (see e.g., Brynjolfsson and Hitt, 1996). The simplest of these methods is production function analysis, which posits a relationship between the output a facility produces and the inputs it consumes. In this case, we consider output to be either revenue or value added (revenue less the cost of purchased materials), and inputs are staff, physical capital and other expenses (materials and purchased services). A number of different relationships can be assumed that connect outputs to inputs, but the simplest form that is commonly used in empirical productivity analysis is the Cobb-Douglas production function. Generically, this equation takes the form:

$$\log Output_{h,t} = \alpha_0 + \beta_{Capital} \log Capital_{h,t} + \beta_{Labor} \log Labor_{h,t} + \beta_{Expense} \log Expenses_{h,t} + year(t) + controls(h,t) + \varepsilon_{h,t}$$

The coefficients (β) represent the percentage change in output per percentage change in an input quantity, and are theoretically expected to be close to the ratio of inputs costs to output costs. Inputs in this formulation can also be subdivided and examined separately. For instance, labor can be divided into nursing staff and other staff and expenses are often divided into materials and purchased services. The output measure is either gross output (overall revenue) or value-added which is revenue less

materials costs. In panel data (repeated observations of the same unit over time), binary variables are included for each year to control for the effect of inflation and different economic conditions in each year. We also include measures that account for how facilities might differ in their ability to convert inputs into outputs. Consistent with the earlier analysis, we include controls for the Quality Score, unionization, location in the NY metropolitan areas, resident mix, number of services, and for-profit status, and competition (bed size is not considered a control since it will serve as the proxy for capital).

Once a reasonable specification for the production function is constructed, researchers add additional variables of interest. An additional variable added to this equation has the interpretation of measuring how that variable is associated with changes in “multifactor productivity” (approximately, the ratio between output and a share weighted sum of inputs including both labor and capital). Following our approach in the prior section, our primary estimating equation is:

$$\log VA_{h,t} = \alpha_0 + \beta_{EMR} UseEMR_h + \beta_{AfterEMR} AfterEMR_{h,t} + \beta_{Capital} \log BedSize_{h,t} + \beta_{Labor} \log LaborExpense_{h,t} + \beta_{Expense} \log OtherExpenses_{h,t} + year(t) + controls(h,t) + \varepsilon_{h,t}$$

We conduct the analysis using two output measures – gross output and value-added (VA) (gross output less materials cost) consistent with prior literature.¹⁷ We proxy capital by Bed Size (see prior discussion). Labor is measured as total labor expense (results are similar when we use full-time equivalent staff). Other expenses are all operating expenses less labor expenses and materials. This category is principally purchased professional services. Production functions are usually estimated using inflation adjusted inputs and outputs. Since all firms are in the same industry and located in the same state they will likely face the same conditions in any given year, so inflation is automatically addressed by the year control variables. However, as a result, we cannot interpret the year variables as representing the overall change in performance of nursing homes over time since it includes both productivity changes and the net effects of output and input price changes.

The *UseEMR* and *AfterEMR* have the same interpretation as before, with the coefficient on the *AfterEMR* term being the primary figure of interest. We also estimate variations of the production function with materials disaggregated from purchased services in various ways. Results are generally consistent regardless of the production function specification, so we utilize the form that is most common in the IT value literature, a value added specification with purchased services (*OtherExpenses*) included as an input, for most of our reporting. This equation is shown above.

We utilize all firms with complete data in our analysis, but restrict the analysis to firms who spend at least 20% of their total expenses on labor. Approximately 12 homes in the sample utilize very few staff on payroll and provide much of their care through contract labor (either to a parent organization or outside agencies). Since none of the Demonstration Project homes operate in this manner, and pooling

¹⁷ Production functions can also be estimated using “physical” output measures – in this case, the total number of resident days. We do not use that approach here for several reasons. First, there is no meaningful way to construct value added measures. Second, resident days are highly correlated with bed size, which means that the capital term dominates the regression and yields unreasonable estimates for other factors. We utilize physical output measures in subsequent analyses where it is more appropriate.

these firms with the other firms give unreliable estimates of primary production function parameters we remove them from the analysis.¹⁸

The primary results from a production function analysis are shown in Table 3a. In Columns 1 to 4 of Table 3 we report output-based and value added production functions with (Cols 2 and 4) and without (Cols 1 and 3) the EMR variables. These regressions contain the full set of controls and use ordinary least squares (OLS) regression with Huber-White clustered standard errors. Examining the Value-added results (column 3) we find the output elasticity of labor to be about 65%, the output elasticity of purchased services to be about 29%, and the output elasticity of capital to be about 9.5%. The labor and purchased services are comparable to their share of value added (66% and 26% in geometric means), which is consistent with economic theory. This gives us greater confidence in the analysis. For control variables we find that for-profit homes are consistently more productive (by ~4.5%, $p < .01$) than not for profit homes consistent with prior work on nursing home productivity. We also find that a 1% increase in Medicaid residents reduces measured productivity by about .3%, which is large and statistically significant. This is likely due to the lower reimbursement rates for Medicaid residents which reduces output when measured in revenue terms. Complaints¹⁹ are also associated with lower productivity ($p < .01$). Other control variables are generally inconclusive. It should also be noted that the sum of the input elasticities (Capital, Labor and Materials) is about 104% which is greater than 1, implying that nursing homes experience increasing returns to scale (IRTS). That is, the home could produce more than (for example) 10% more output by increasing all inputs by 10%. This is unusual, since operating under IRTS is not efficient (rational managers should expand their facilities until there are no increasing returns), but it is not surprising given restrictions on capital investment due to “certificate of need”²⁰ laws. The production function estimates are robust to this characteristic, although this observation will be important in selecting suitable efficiency models later in the analysis.

When we introduce variables for EMR adoption, we find modest positive but statistically insignificant effects. The typical EMR adopter is 0.2% to 0.4% more productive (not significant) than the rest of the sample across all models. The coefficient on *AfterEMR* is about 1.1% in both value-added and output based specifications (columns 2 and 4 of Table 3a). However, in both cases the standard errors are as large or larger than the estimate so these figures are not statistically significantly different from zero (the confidence interval runs from about -1% to +2%). Restricting the sample to demonstration project

¹⁸ The distribution of the ratio of labor to total expenses is bimodal with a cutoff between the modes of about 40% - homes either use mostly staff or mostly contract labor. A home might also show variation in this measure due to data error. Experiments with different cutoffs show that production function estimates are reliable down to a threshold of 20%. To maximize the sample and limit the number of ad-hoc assumptions, we use the 20% threshold. This reduces the sample by 62 observations from 11 facilities.

¹⁹ Since Complaints and Deficiencies have highly skewed distributions, we log transform these variables. For example $\text{LogComplaints} = \log(1 + \text{Complaints})$. The added 1 is due to the fact that many homes have 0 complaints and would therefore become missing data if log transformed directly.

²⁰ Nursing home capacity in New York (and in many other states) is carefully regulated through the certificate of need (CON) process. Before a facility is allowed to make a major capital investment they must apply for approval from the state. The motivation is that process can prevent overcapacity which would raise operating costs which are ultimately reimbursed by the state through Medicaid. It should be noted, however, that capacity utilization in this industry is quite high, suggesting that this indeed acts as a capacity constraint.

homes alone (Table 3b) provides acceptable estimates of the production function parameters but not the EMR coefficients. The point estimates of EMR adopters is now 4.5% but the *AfterEMR* coefficient is negative -3.2% (see Table 3b, column 2). This appears to be due to multicollinearity, with the large *UseEMR* coefficient forcing a negative value of the *AfterEMR* coefficient to an amount that nets close to +1% (as in the previous analysis), so the results cannot be taken as valid point estimates. The coefficient turns positive again when we restrict the sample to the demonstration project homes (Table 3b column 3) but is very imprecisely estimated and not significant.

The results are not substantially affected by how we subdivide production inputs. We also attempted instrumental variables regressions using the inhibitors of investment questions from the survey as instruments for *UseEMR* and *AfterEMR*. They did not have sufficient first stage power to provide reliable estimates and are therefore omitted. The lack of predictive power between barriers to IT adoption and actual EMR adoption may be due to the fact that adoption of EMR is a wholesale change to the technology infrastructure of a nursing home, in contrast to other settings where this scale has proven useful which involved changes in the level of investment on the margin.

Overall, the baseline productivity results suggest that there may be a small positive benefit of EMR when implemented in the population, but the results are inconclusive. Since some estimates place the long-run annual operating costs of an EMR system to be about 0.5% of operating costs (Savage and Gutkind, 2011), the point estimates suggest that it is plausible that EMR systems at least earn back their operating costs.²¹

Analysis: Extension – The Role of Organizational Practices on the Value of EMR Adoption

We extend our baseline productivity model to consider the possibility that complementarities between organizational factors and EMR adoption influence productivity. That is, EMR may have a small effect when implemented alone, but becomes more valuable when implemented in organizations that either change to adopt progressive work practices, or were already endowed with these practices. Since we do not have panel data on organizational structure we cannot distinguish these explanations but anecdotal evidence from the demonstration project suggests that progressive work practices are due to both existing home characteristics and deliberate investment in organizational change.

There are a number of potential theoretical reasons for this relationship. Generally, organizations with decentralized work practices may be better at utilizing information in production, especially in those organizations that support information sharing and teamwork. Moreover, individuals with greater levels of skill combined with greater levels of autonomy may be better able to adapt to technology enabled work practices. Related work (Avgar, Tambe, and Hitt, 2011) found that homes that have these

²¹ The exact return depends heavily on how much of EMR costs are reimbursed. Demonstration project homes do not pay operating costs for their systems, and many other homes can include EMR costs as part of operating costs subject to reimbursement. However, once the productivity gain exceeds expected operating costs, the benefits of EMR outweigh the costs regardless of whether they are included in reported costs, reimbursed or not included at all. Worst case, they are not included so a 0.5% is breakeven under any set of assumptions. However, given the large standard errors of these estimates, we cannot be certain that the actual returns are greater than breakeven.

practices have lower technology support costs which may be consistent with them being better able to adopt the system.

To accomplish this analysis, we utilize the variable *Progressive* which is the index of progressive work practices discussed earlier. This variable is entered in levels, to account for the fact that homes using these practices may be more or less productive generally, as well as the interactions *UseEMR*Progressive* and *AfterEMR*Progressive*. Significant values from these variables suggest that progressive homes that use EMR have higher productivity (*UseEMR*Progressive*) overall, and that EMR implementation has a greater positive effect on productivity when implemented in homes that use progressive work practices (*AfterEMR*Progressive*). It is this latter variable which is of most interest along with the direct *AfterEMR* variable. Thus we estimate:

$$\log VA_{h,t} = \alpha_0 + \beta_{EMR} UseEMR_{h,t} + \beta_{AfterEMR} AfterEMR_{h,t} + \beta_{Prog} Progressive + \beta_{ProgEMR} Progressive * UseEMR + \beta_{ProgAfterEMR} Progressive * AfterEMR \\ + \beta_{Capital} \log BedSize_{h,t} + \beta_{Labor} \log LaborExpense_{h,t} + \beta_{Expense} \log OtherExpenses_{h,t} + year(t) + controls(h,t) + \varepsilon_{h,t}$$

The results of this analysis are summarized in the later columns of Table 3a (Columns 5-10 for different econometric models) and Table 3b (Columns 4-6 for different subsamples). Overall, while the direct effect of EMR implementation is similar in this analysis to the prior analysis (inconclusive), we find a substantial and positive effect of EMR when adopted in progressive homes. In the specification comparable to earlier results, we find that facilities that are one standard deviation above the mean on the Progressive score are 1.3% to 1.6% more productive (that is, $\beta_{ProgAfterEMR} = 1.31\%$, $p < .05$ in Column 5, and $\beta_{ProgAfterEMR} = 1.65\%$, $p < .01$ in Column 6). Absent EMR, progressive homes are no more productive than any other homes. In addition, homes that later adopt EMR and are high on the progressive scale are not significantly more productive prior to EMR implementation (although the point estimate is positive). Restricting the sample to demonstration project homes, this coefficient is also positive (1.0 - 1.2%) but not significant.²² Across the remaining columns of Table 3a, this result does not appear to be sensitive to different econometric specifications, although some models yield similar point estimates that are statistically insignificant. In Table 3b (columns 5 and 6) we find that this result also appears when the sample is restricted to the demonstration project homes, although the result shown in column 5 is not significant and the result in column 6 is directionally consistent but implausibly large. Both issues with demonstration project homes are likely due to the reduced sample size.

Collectively, these results provide evidence of complementarities between EMR use and progressive work practices. That is, firms that adopt EMR and either have or change to more progressive work practices gain greater benefits from their EMR investments.

Analysis: Cost Functions

While production functions are commonly used in the IT-productivity literature, they are less common in healthcare economics studies because they are limited to only considering a single output. In general,

²² Since not all homes in the demonstration project participated in the survey, we instead used the progressivity score from the research project on labor effects. This measure is similar to ours but includes more components and has a somewhat greater emphasis on quality of worklife issues (Avgar and Lipsky, 2010).

most healthcare facilities provide a variety of outputs such as serving patients or residents with different types of care needs. In addition, cost functions may be more appropriate when the quantity of output is largely fixed (e.g. there is fixed capacity and capacity utilization is practically 100%) and cost minimization is an important managerial goal in driving performance. There are two standard ways in which multi-output production has been modeled in nursing homes: cost functions and efficiency analysis.

The cost function approach utilizes the same underlying economics as production functions, although the simple Cobb-Douglas form is no longer appropriate since it does not allow for sufficiently rich relationships between input quantities and input costs.²³ As a result, we will estimate a transcendental logarithmic (translog) cost function with two variable inputs (Labor and Expenses), one fixed input (Capital, proxied by Bed Size) and three outputs – Medicare Resident Days, Medicaid Resident Days and Private Pay Resident Days. We will include the same control variables as before (for-profit, union, number of services, NY Metro area, QualityScore, DeficiencyScore, ComplaintScore) except for the resident proportion measures which are already subsumed in the outputs. The translog cost function contains first order (linear), squared, and interaction terms between all inputs and outputs.

In cost functions, variable inputs are represented by their prices, which is computed as the cost of the inputs divided by the number of input units (for labor, the input units are FTE employees; for expenses, it is number of resident-days). For fixed inputs, these are introduced in levels so our measure of capital is bed size. Outputs in cost functions are typically measured in “physical units”, in this case the number of resident days of each type of resident. The primary dependent variable is total variable costs which is equal to labor, materials and purchased services costs (capital costs such as depreciation and non-operating expense are excluded). Cost functions can be estimated directly, or combined with a cost function system that also includes the demand functions for each variable input that share some common coefficients. Estimating a system can be more efficient in a statistical sense, although it is also common to not do so in empirical work. Since there are only two variable inputs and the total input share must sum to one, we can either estimate the input equation for labor or materials (the coefficients of the other are entirely determined by the one estimated). The EMR adoption variables can then be added to the cost function and the labor demand equation as before.

The results of this analysis are shown in Table 4. We estimated both cost functions and labor demand equations. However, none of the EMR variables were large or significant in the labor demand equations, they are not presented. In Table 4, Columns 1 and 3 show the relationship between EMR costs and the *AfterEMR* variable in the full sample (Column 1) and in the demonstration project alone sample (Column 3). When the EMR variables are introduced in isolation, the results suggest that nursing

²³ Every production function has a “dual” equivalent cost function. For the Cobb-Douglas, this cost function turns out to be uninteresting since it involves the cost shares for each input being restricted to a constant that does not vary across facilities, time or any other factor. As a result, cost function studies generally utilize the transcendental logarithmic cost (translog) and production function since that provides terms to allow facilities to substitute between different inputs at varying rates. The translog function nests the Cobb-Douglas function as a special case. See Varian (1990) for a textbook discussion of the theory underlying production economics or Berndt (1982) for a discussion of the practice of estimating cost functions.

homes that adopt EMR experience a 2.7% rise in costs ($p < .1$) above the ~1.4% (not significant) difference in cost between EMR adopters and non-adopters that is present before and after adoption. However, homes that are one standard deviation higher on the *Progressive* work practice scale have costs that are 2.4% lower than other homes after EMR implementation ($p < .05$) which almost entirely offsets the cost increase associated with EMR adoption. Progressive homes also have significantly lower costs (-2.2%, $p < .05$ in the full sample and -2.4% in the demonstration project sample $p < .1$). These results also appear in fixed effects and random effects panel models (not shown) – the coefficients are somewhat smaller but still significant. The results are also the same whether we include or exclude the controls. Among the control variables, for-profit homes have significantly lower costs (about 7.5% lower, $p < .001$). There is no apparent effect of quality, location, unionization or competition on cost.

These results suggest that EMR implementation is associated with a rise in costs but that these costs are largely offset in homes that utilize progressive work practices. These results are consistent with the prior analysis of production functions in terms of organizational complementarities, but suggest (in contrast) that EMR adoption by itself may increase costs, at least in the short run.

Analysis: Efficiency Analysis

There have been a number of nursing home productivity studies that have utilized efficiency analysis methods. Essentially the procedure attempts to find the homes that are efficient in the sense that they produce the maximum amount of some combination of outputs given a quantity of inputs utilized. Each home then receives an efficiency score as the “distance” distance from this frontier. Efficiency scores range from 0 to 1 with 1 being fully efficient as discussed earlier.

DEA analysis proceeds in two steps. First, efficiency scores are calculated for each facility in each year given a set of inputs and outputs. Second, regression analysis is used to examine how efficiency scores vary with variables of interest such as EMR adoption, for-profit status, location, service breadth and unionization (quality and output mix in this analysis can be handled with outputs). A critical tradeoff required for DEA analysis is choosing an appropriate set of inputs and outputs that capture the richness of the production process, while not having so many variables that homes cannot be compared to each other directly. With too many outputs and inputs, all homes appear on the efficient frontier because no two homes have exactly the same input-output composition. After some experimentation, we settled on a DEA model with four outputs: Medicare, Medicaid and Private resident-days (three outputs) and the Quality Measures Score (*QualityScore*, one additional output). For inputs we include staff and expenses. We originally disaggregated materials and purchased services, and disaggregated labor into different types of nursing, administrators, other medical staff, and other employees. However, this yielded too many of the homes being coded as efficient. We therefore reduced the input set to include the number of FTEs for Nurses (RN/LPN), CNAs, and all other staff, along with total non-labor expense (a total of 4 inputs). After cleaning the data to ensure that the staffing and expense data were all self-consistent and reasonable, we estimated DEA scores for each home in each year from 2004 to 2009 using the input oriented variable returns to scale DEA model (Banker, Charnes and Cooper, 1984). The variable returns to scale model was chosen because the productivity analysis suggested that the data do not show constant returns to scale, and we chose an input oriented approach because capacity is not really under

the control of nursing home managers. The actual estimates were performed using DEAP.²⁴ This package was chosen because it is free, implemented the required models, and could rapidly compute the DEA scores for the 200 decision making units available in each year which is somewhat “large” for a DEA model.

We then estimated models of the form:

$$EfficiencyScore_{h,t} = \alpha_0 + \beta_{EMR} UseEMR_h + \beta_{AfterEMR} AfterEMR_{h,t} + year(t) + other\ controls + \varepsilon_{h,t}$$

The controls in this regression are as before (omitting quality and resident mix which are already part of the output set). Estimates were done using ordinary least squares with Huber-White robust standard errors. We also report standard errors done by 50 samples of bootstrap estimation – some authors have argued that bootstrap errors are more reliable because the DEA procedure induces statistical dependence among efficiency scores in complex ways since homes are measured as a distance (in input-output space) relative to other homes. However, there is no panel data equivalent of this approach which we could utilize here, and a failure to correct for repeated observations of similar units makes the estimated standard errors too small (by as much as the square root of the number of time observations per unit), and therefore must be interpreted conservatively.

The results of this analysis are shown in Table 5. The results here are somewhat more favorable to EMR adoption than the prior estimates. The efficiency analysis suggests that EMR adoption raises efficiency by about 3.1% ($p < .05$) (see especially Table 5, column 1). When we add additional variables that measure organization, we find that Progressive homes get an additional 1.74% of efficiency benefit but this difference is only borderline significant, and then only with bootstrap standard errors. The control variables suggest that for-profit homes are about 5% more efficient, while those that operate in the NY metro area are measured to be less efficient, probably because of higher services costs in New York City which raise the cost of “other expenses”. Thus, these results are generally consistent with prior results although the impact of Progressive work practices is less clear.

Summary and Recommendations

Overall, we find support for the argument that the implementation of electronic medical records improves productivity and efficiency in homes that adopt complementary (progressive) work practices and mixed evidence for the general impact of EMR in the overall population. Productivity analysis and efficiency analysis suggest positive benefits on the order of 1-2.5% improvements in efficiency although the confidence intervals on these estimates are substantial and in many cases the marginal effects are not statistically distinguishable from zero. Economic cost function analyses find that costs may increase following EMR adoption but these costs are offset in homes that use progressive work practices. These results are robust to controlling for most of the known determinants of nursing home performance identified in the prior literature, and are not due to preexisting differences between the homes that eventually adopt EMR and those that do not.

²⁴ By T. Coelli – see <http://www.uq.edu.au/economics/cepa/deap.htm>.

In terms of the original research questions, our results suggest that EMR systems are a good investment from a private standpoint in homes that have adopted or can adopt progressive work practices. Using figures from the productivity or efficiency analyses, a 1.5% increase in productivity or efficiency translates into an incremental ~\$5/bed-day increase in operating margins for the homes in our sample that are one standard deviation above the mean in the progressive score (roughly the top third of homes on this dimension). This is roughly three times the estimated long term cost of EMR (although this exact figure will likely vary by home, system and other factors). In the worst case, the cost function analysis suggests that EMR systems are break-even. These observations become more favorable if the EMR variable costs can be recovered in the payment system.

The results are more mixed for the average facility. Efficiency analysis suggests there is a potentially substantial private benefit (+3% efficiency with a confidence interval of roughly 0 to 6%) and a productivity analysis suggests that most firms would break even or perform slightly better with EMR systems in place (+1% efficiency with a -1% to 3% confidence interval). However, these homes will likely experience higher costs which will attenuate benefits, there is high variance in the returns, and the returns in some homes will undoubtedly be negative. Again, if these higher costs can be recovered through the reimbursement process, this makes the investment more likely to have positive returns.

From a social standpoint, the results are also mixed. Productivity benefits incorporate increases in revenue as well as costs so are not necessarily a good guide for social investment decisions because they combine revenue enhancements, which are just transfers, with efficiency gains which are welfare increasing. Coupled with the observation that these homes are able to attract more private pay residents, a substantial portion of the benefit may be coming from higher revenues rather than reduced costs. This may also partially explain the efficiency results if homes are raising output along the private pay dimension. However, since homes cannot discriminate between the care they give to residents, investments that make the home more attractive to private pay residents will likely improve quality for all residents, possibly in ways that cannot be easily captured by aggregate readings of the quality measures that we consider. Whether this is worth potentially higher costs is a question of balancing policy priorities and will likely require more detailed study over a longer time period.

An additional observation is that it is challenging to separate the effect of EMR implementation from the variance in measured performance due to other factors. Performance ratio analysis is simply too imprecise, and methods that have proven useful in aggregate performance studies do not have sufficient resolution to offer concrete results for the population as a whole, much less the results that were experienced by a particular facility. This would suggest that the investment justification for an individual home should not rely on hitting targets for aggregate cost or changes in quality measures. Instead, given that EMR costs are typically on the order of 1% of operating expense, it is likely that the EMR investment can be justified by savings in specific initiatives that can be facilitated by EMR such as streamlined documentation processes, reduced medications usage, or other micro-level initiatives that can collectively yield cost savings. This is likely to be especially important for homes that are unable or unwilling to adopt the types of work systems that increase the returns to EMR.

It may also be the case that relatively small changes in quality of care can lead to substantial financial benefits in the area of hospitalization avoidance which can be investigated once significant post-implementation hospitalization data on nursing home residents becomes available. However the majority of these gains accrue to residents and third-party payers rather than the nursing home (with perhaps the exception of reduced bed reservation costs) so are unlikely to affect the private decision of a nursing home operator to adopt EMR.

It is worth noting that these results are based on a limited amount of post-implementation information (about 1-2 years for a typical facility in our sample), and that like other IT implementations, benefits may take some time to materialize (consistent with some of our analysis using lagged values and matching estimators), and some types of benefits such as reduced hospitalization cannot yet be measured.

Recommendations

The observations made in this analysis lead to the following recommendations:

- Consider adopting EMR along with changes to work practices that promote individual decision making, teamwork, and process improvement to make greater use of the information provided by the system. Facilities with progressive work practices consistently show higher returns to EMR adoption and on average, these higher returns appear to exceed the average costs of EMR system implementation and operation.
- Maintain reasonable expectations on the facility-wide cost and quality impact of EMR adoption. While there is some evidence that EMR adoption has efficiency benefits on average, the range of plausible estimates of efficiency improvements over the first two years following implementation are on the order of 1-3%. This is unlikely to be easily observable when examining the facility as a whole. Performance benefits may become more apparent over time as is typical with IT investments.
- Recognize that there appears to be limited financial downside to EMR implementation. The results in this analysis suggest an up to 3% increase in costs (which may be offset by increased revenue from private pay residents), and a range of productivity or efficiency changes on the order of 0 to 3% which account for both costs and increased revenue. Consequently, it may be possible for the system to be paid for through specific benefits from automation such as reduced paperwork, reduced medication administration, or by intangible benefits such as improved employee retention or quality improvements that are substantial but too small to be easily observed in the QI/QM measures. If costs can be recaptured through the payment system, it is even more favorable. While the results in this study suggest that the overall average benefits are modest, there is also no evidence that EMR implementations create a substantial negative financial impact.

Table 1: Samples and Means of Major Variables

	Full Sample	Dem Project vs. Controls	Dem. Project Only
<u>EMR Adoption</u>			
Use EMR	53.1%	15.0%	100.0%
<u>Production Inputs/Outputs</u>			
Output (thousands)	\$ 16,750	\$ 17,114	\$ 21,012
Value Added (thousands)	\$ 11,102	\$ 11,012	\$ 13,014
Efficiency	92.3%	92.7%	89.6%
Employment Expense	\$ 9,991	\$ 9,904	\$ 11,936
Employment (FTE)	202.9	191.1	204.5
Nurses	121.3	116.3	127.6
Materials (thousands)	\$ 1,399	\$ 1,429	\$ 1,819
Purchased Services (thousands)	\$ 3,821	\$ 4,223	\$ 5,449
Bed Size	178.21	181.23	211.83
<u>Quality</u>			
Quality Score	74.66	73.29	67.24
Complaint Score	10.95	10.36	0.31
Deficiency Score	20.37	23.67	12.63
<u>Prices</u>			
Medicare Price (\$/bed day)	\$ 457	\$ 463	\$ 427
Medicaid Price (\$/bed day)	\$ 206	\$ 213	\$ 247
Overall Avg. Price (\$/bed day)	\$ 281	\$ 292	\$ 306
Labor Price (\$/person-year)	\$ 50,688	\$ 53,111	\$ 58,642
Materials/Svcs. Price (\$/bed day)	\$ 99	\$ 103	\$ 105
<u>Margins</u>			
Gross Margin (no admin)	8.44%	8.62%	8.04%
Gross Margin	6.67%	6.79%	6.13%
<u>Other Controls</u>			
For Profit	53.6%	68.4%	94.1%
Union	59.9%	73.7%	94.1%
NY Metro (%)	28.99%	35.96%	58.82%
Medicare Bed Days (%)	11.2%	11.6%	11.4%
Medicaid Bed Days (%)	73.9%	75.6%	79.2%
Competition Index (0-1)	6.24%	5.67%	4.75%
<u>Sample Sizes</u>			
Facilities (in 2009, maximum)	207	114	17
Observations (all years, maximum)	1,207	645	98

Production inputs are computed in geometric means. Rest are arithmetic means.

Table 2a: Summary of Before-After Ratio Analysis

		Base	Base + Quality & Size Controls	Fixed Effects
Staffing				
All Staff (FTEs)	Full Sample	0	0	0
	Demo vs. Sample	-	-	-0.0733 (p<.05)
	Demo Project Only	0	+	0
Nurses (CNAs, LPNs, RNs) (FTEs)	Full Sample	0	0	0
	Demo vs. Sample	-	-	-0.0982* (p<.05)
	Demo Project Only	0	+	0
Financial				
Gross Margins (excl Admin) (% margin)	Full Sample	+	+	+
	Demo vs. Sample	-	-	-0.0267 (p<.10)
	Demo Project Only	0	0	0
Gross Margins (% margin)	Full Sample	+	+	+
	Demo vs. Sample	-	-	-0.0251 (p<.10)
	Demo Project Only	0	0	0
Average Medicare Rate (\$/resident-day)	Full Sample	-30.07 (p<.05)	-	0
	Demo vs. Sample	0	0	0
	Demo Project Only	81.62 (p<.05)	+	38.67 (p<.05)
Average Medicaid Rate (\$/resident-day)	Full Sample	-14.51 (p<.05)	-	0
	Demo vs. Sample	+	11.19 (p<.05)	0
	Demo Project Only	33.83 (p<.10)	0	+
Overall Average Rate (\$/resident-day)	Full Sample	-46.24* (p<.05)	-28.78* (p<.05)	-
	Demo vs. Sample	-	0	0
	Demo Project Only	0	+	+
Quality				
Complaints Score (Index, lower is better)	Full Sample	0	0	+
	Demo vs. Sample	0	0	0
	Demo Project Only	0	0	0
Deficiency Score (Index, lower is better)	Full Sample	0	0	0
	Demo vs. Sample	0	0	0
	Demo Project Only	0	0	0
Quality Indicators Score (Index, higher is better)	Full Sample	3.504 (p<.10)	0	0
	Demo vs. Sample	+	0	0
	Demo Project Only	+	+	0
Resident Composition				
Percent Residents Medicare (% of all residents)	Full Sample	0	0	0
	Demo vs. Sample	0	0	-
	Demo Project Only	+	0	0
Percent Residents Medicaid (% of all residents)	Full Sample	-0.0280 (p<.05)	0	0
	Demo vs. Sample	0	0	+
	Demo Project Only	-0.0938 (p<.10)	-	-
Percent Residents Private (% of all residents)	Full Sample	0.0298 (p<.05)	+	0
	Demo vs. Sample	0	0	0
	Demo Project Only	0.0567 (p<.10)	0.0362 (p<.10)	+

Sample: All facilities in survey; 0 indicates t-statistics less than 0.5; +/- are not significant but t-statistics>0.5
Time Period 2004-2009

Table 3a: Baseline Production Functions

VARIABLES	(1) Output Base	(2) Output DID	(3) ValueAdded Base	(4) ValueAdded DID	(5) Output DIDOrg	(6) ValueAdded DIDOrg	(7) ValueAdded RE	(8) ValueAdded FE	(9) ValueAdded FlexCov	(10) ValueAdded Quantile
Use EMR		0.00360 (0.0109)		0.00606 (0.0125)	0.00200 (0.0109)	0.00415 (0.0128)	0.000125 (0.0129)		-0.00874 (0.0131)	0.00588 (0.00715)
After EMR		0.0108 (0.0112)		0.0113 (0.0124)	0.00904 (0.0109)	0.00932 (0.0122)	0.00887 (0.00839)	0.00796 (0.00858)	0.0153** (0.00748)	0.0131 (0.00842)
Progressive					-0.00727 (0.00596)	-0.00755 (0.00679)	-0.00538 (0.00829)		-0.00598 (0.00853)	-0.00839** (0.00396)
Use EMR x Progressive					0.00941 (0.00754)	0.0105 (0.00877)	0.00883 (0.0122)		0.00636 (0.0124)	0.0140** (0.00666)
After EMR x Progressive					0.0139*** (0.00530)	0.0175*** (0.00637)	0.0105 (0.00781)	0.00901 (0.00802)	0.0105 (0.00711)	0.0137* (0.00764)
log(Employee Expense)	0.582*** (0.0254)	0.581*** (0.0257)	0.659*** (0.0337)	0.657*** (0.0342)	0.593*** (0.0266)	0.673*** (0.0362)	0.654*** (0.0191)	0.546*** (0.0329)	0.638*** (0.0192)	0.661*** (0.0113)
log(Purchase Services)			0.287*** (0.0248)	0.289*** (0.0246)		0.285*** (0.0261)	0.246*** (0.00962)	0.202*** (0.0124)	0.219*** (0.00927)	0.303*** (0.00661)
log(Materials & PS)	0.371*** (0.0165)	0.372*** (0.0162)			0.369*** (0.0160)					
log(Capacity)	0.0749** (0.0340)	0.0729** (0.0346)	0.0848** (0.0384)	0.0825** (0.0390)	0.0579 (0.0351)	0.0640 (0.0397)	0.134*** (0.0252)	0.229*** (0.0625)	0.184*** (0.0260)	0.0629*** (0.0141)
For Profit	0.0479*** (0.0107)	0.0487*** (0.0105)	0.0541*** (0.0122)	0.0552*** (0.0120)	0.0478*** (0.0109)	0.0546*** (0.0125)	0.0488*** (0.0124)	0.0791*** (0.0304)	0.0334*** (0.0127)	0.0435*** (0.00644)
Union	-0.00296 (0.0121)	-0.00160 (0.0125)	-0.00159 (0.0138)	0.000106 (0.0142)	-0.000221 (0.0130)	0.00122 (0.0149)	-0.0147 (0.0122)	-0.0273 (0.0195)	-0.00122 (0.0130)	0.0139* (0.00727)
QualityScore	-0.000390 (0.000259)	-0.000388 (0.000254)	-0.000389 (0.000304)	-0.000384 (0.000298)	-0.000443 (0.000269)	-0.000449 (0.000316)	-0.000468** (0.000232)	-0.000526** (0.000257)	-0.000242 (0.000216)	-0.000218 (0.000190)
ComplaintScore	-0.000234*** (6.42e-05)	-0.000235*** (6.37e-05)	-0.000262*** (7.44e-05)	-0.000263*** (7.39e-05)	-0.000234*** (6.54e-05)	-0.000263*** (7.54e-05)	-0.000224*** (5.89e-05)	-0.000175*** (6.20e-05)	-0.000144*** (5.00e-05)	-0.000195*** (5.44e-05)
DeficiencyScore	3.62e-05 (5.93e-05)	4.27e-05 (6.03e-05)	4.55e-05 (6.69e-05)	5.38e-05 (6.80e-05)	3.25e-05 (5.77e-05)	4.46e-05 (6.54e-05)	5.11e-05 (6.66e-05)	5.23e-05 (6.94e-05)	7.65e-05 (5.61e-05)	3.38e-05 (6.37e-05)
NYMetro	0.0288* (0.0168)	0.0293* (0.0167)	0.0370* (0.0203)	0.0374* (0.0203)	0.0260 (0.0193)	0.0345 (0.0238)	0.0693*** (0.0175)		0.0795*** (0.0179)	0.00664 (0.00877)
PctMedicare	0.0323 (0.117)	0.0408 (0.117)	-0.0206 (0.137)	-0.0112 (0.139)	-0.00374 (0.116)	-0.0646 (0.137)	0.178* (0.108)	0.333** (0.158)	0.237** (0.105)	-0.0732 (0.0654)
PctMedicaid	-0.335*** (0.0545)	-0.328*** (0.0545)	-0.416*** (0.0697)	-0.408*** (0.0698)	-0.322*** (0.0537)	-0.401*** (0.0691)	-0.363*** (0.0595)	-0.345*** (0.0928)	-0.356*** (0.0591)	-0.323*** (0.0350)
herfindahl	0.0824 (0.0522)	0.0781 (0.0526)	0.0914 (0.0638)	0.0866 (0.0637)	0.0692 (0.0514)	0.0757 (0.0617)	0.0447 (0.0510)	0.0726 (0.0551)	0.0315 (0.0471)	0.0714* (0.0398)
Year 2004	-0.00959 (0.00964)	-0.00370 (0.0123)	-0.00569 (0.0109)	0.000599 (0.0137)	-0.00440 (0.0124)	-0.000304 (0.0139)	-0.0104 (0.00964)	-0.0376*** (0.0109)	-0.0150 (0.0105)	-0.000386 (0.0106)
Year 2005	-0.0128 (0.00833)	-0.00920 (0.00972)	-0.00974 (0.00932)	-0.00590 (0.0108)	-0.00862 (0.00999)	-0.00547 (0.0111)	-0.0137 (0.00867)	-0.0349*** (0.00948)	-0.0193** (0.00884)	0.00524 (0.00988)
Year 2006	0.00866 (0.00877)	0.0119 (0.00991)	0.0142 (0.0108)	0.0175 (0.0120)	0.00947 (0.0103)	0.0145 (0.0122)	0.00524 (0.00840)	-0.0122 (0.00885)	-0.000250 (0.00931)	0.00918 (0.00971)
Year 2006	-0.0137** (0.00665)	-0.0117 (0.00719)	-0.0154** (0.00778)	-0.0133 (0.00842)	-0.0113 (0.00747)	-0.0133 (0.00876)	-0.0155* (0.00803)	-0.0249*** (0.00813)	-0.0164** (0.00815)	-0.00840 (0.00954)
Year 2008	0.00242 (0.00623)	0.00381 (0.00615)	0.00362 (0.00683)	0.00504 (0.00680)	0.00650 (0.00637)	0.00779 (0.00708)	0.00373 (0.00771)	4.54e-05 (0.00762)	0.00502 (0.00815)	0.00325 (0.00929)
Observations	1,212	1,212	1,212	1,212	1,124	1,124	1,124	1,124	1,124	1,124
R-squared	0.985	0.985	0.980	0.980	0.986	0.981		0.651		
Number of Homes							203	203	203	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3B: Productivity Regressions (Preferred Model/Varying Sample)

VARIABLES	(1) ValueAdded Full Sample	(2) ValueAdded DP vs. Control	(3) ValueAdded DP Only	(4) ValueAdded Full Sample	(5) ValueAdded DP vs. Control	(6) ValueAdded DP Only
Use EMR	0.00393 (0.0125)	0.0464* (0.0252)		0.00175 (0.0129)	0.0466 (0.0361)	
After EMR	0.0111 (0.0124)	-0.0331 (0.0241)	0.0391 (0.0381)	0.00842 (0.0123)	-0.0676 (0.0482)	0.0140 (0.0433)
Progressive				-0.00805 (0.00672)	-0.00593 (0.00722)	-0.153*** (0.0391)
Use EMR x Progressive				0.0119 (0.00853)	-0.00403 (0.0370)	
After EMR x Progressive				0.0165*** (0.00619)	0.0138 (0.0265)	0.0560** (0.0237)
log(Employee Expense)	0.651*** (0.0340)	0.650*** (0.0360)	0.569*** (0.114)	0.665*** (0.0359)	0.658*** (0.0371)	0.388* (0.177)
log(Purchase Services)	0.289*** (0.0245)	0.328*** (0.0173)	0.348*** (0.0338)	0.285*** (0.0259)	0.324*** (0.0164)	0.283*** (0.0533)
log(Capacity)	0.0917** (0.0400)	0.0546 (0.0541)	0.205 (0.152)	0.0744* (0.0409)	0.0365 (0.0559)	0.111 (0.302)
For Profit	0.0515*** (0.0118)	0.0385** (0.0159)	0.00512 (0.0845)	0.0503*** (0.0123)	0.0361** (0.0175)	
Union	0.000144 (0.0142)	-0.0108 (0.0166)	-0.143** (0.0594)	0.00132 (0.0149)	-0.00486 (0.0181)	
QualityScore	-0.000401 (0.000295)	-0.000347 (0.000344)	-0.000732 (0.00113)	-0.000466 (0.000312)	-0.000348 (0.000386)	-0.00356 (0.00207)
ComplaintScore	-0.00957*** (0.00343)	-0.00899** (0.00428)	-0.00308 (0.00618)	-0.0100*** (0.00348)	-0.00907* (0.00458)	0.00561 (0.00905)
DeficiencyScore	-0.00244 (0.00260)	0.000920 (0.00299)	0.0167** (0.00606)	-0.00361 (0.00264)	-0.000603 (0.00323)	0.000341 (0.0123)
NYMetro	0.0341* (0.0201)	0.00496 (0.0184)	0.0573 (0.0507)	0.0300 (0.0235)	0.00570 (0.0216)	0.483*** (0.107)
PctMedicare	0.00194 (0.137)	0.0298 (0.165)	1.238 (0.821)	-0.0488 (0.136)	-0.0126 (0.171)	3.106** (1.185)
PctMedicaid	-0.399*** (0.0677)	-0.406*** (0.0938)	-0.0313 (0.538)	-0.389*** (0.0666)	-0.395*** (0.0981)	-0.250 (0.772)
herfindahl	0.0919 (0.0639)	0.152 (0.118)	0.419 (0.273)	0.0806 (0.0616)	0.117 (0.115)	-0.227 (0.556)
Year 2004	-0.00375 (0.0139)	0.00751 (0.0153)	0.0743 (0.0433)	-0.00555 (0.0140)	0.00577 (0.0157)	-0.0169 (0.0670)
Year 2005	-0.00917 (0.0111)	-0.0116 (0.0134)	0.0856** (0.0373)	-0.00911 (0.0113)	-0.0109 (0.0143)	0.00536 (0.0693)
Year 2006	0.0161 (0.0119)	0.0127 (0.0116)	0.113** (0.0475)	0.0129 (0.0121)	0.00731 (0.0122)	0.0365 (0.0891)
Year 2006	-0.0121 (0.00858)	-0.0143 (0.0101)	0.0445 (0.0388)	-0.0124 (0.00891)	-0.0181* (0.0104)	0.00110 (0.0868)
Year 2008	0.00587 (0.00687)	0.00661 (0.00940)	0.0242 (0.0471)	0.00874 (0.00711)	0.00807 (0.0106)	0.0208 (0.0934)
Observations	1,212	645	98	1,124	562	49
R-squared	0.980	0.984	0.957	0.981	0.984	0.921

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Cost Function Estimates

(Note: interaction terms and intercept not shown)

VARIABLES	1	2	3	4
	Full Smpl Cost EMR Only	Full Smpl Cost EMR & Prog	DP v. Controls Cost EMR Only	DP v. Controls Cost EMR & Prog
Use EMR	0.0142 (0.0174)	0.0153 (0.0172)	0.00952 (0.0303)	0.00580 (0.0302)
After EMR	0.0267* (0.0148)	0.0295** (0.0145)	0.0324 (0.0205)	0.0324 (0.0214)
Progressive		-0.0224** (0.00942)		-0.0235** (0.0107)
Use EMR x Progressive		0.0216* (0.0113)		0.0326 (0.0351)
After EMR x Progressive		-0.0237*** (0.00800)		0.00305 (0.0276)
log(Output Medicare)	0.108*** (0.0202)	0.105*** (0.0198)	0.110*** (0.0251)	0.113*** (0.0239)
log(Output Medicaid)	0.458*** (0.0898)	0.446*** (0.0862)	0.377*** (0.104)	0.401*** (0.0959)
log(Output Private Pay)	0.131*** (0.0178)	0.128*** (0.0170)	0.108*** (0.0221)	0.112*** (0.0213)
log(Capacity)	0.273** (0.118)	0.284** (0.113)	0.360** (0.140)	0.321** (0.132)
ForProfit	-0.0751*** (0.0147)	-0.0764*** (0.0145)	-0.0765*** (0.0222)	-0.0739*** (0.0211)
Union	-0.0219 (0.0176)	-0.0152 (0.0179)	-0.0270 (0.0233)	-0.0159 (0.0238)
Quality Score	-2.19e-05 (0.000368)	9.19e-05 (0.000370)	-2.48e-05 (0.000507)	7.70e-05 (0.000496)
Complaint Score	-0.00244 (0.00377)	-0.00241 (0.00371)	0.000198 (0.00461)	0.00107 (0.00436)
Deficiency Score	-0.00274 (0.00318)	-0.00363 (0.00317)	-0.00384 (0.00454)	-0.00541 (0.00457)
NYMetro	-0.0186 (0.0260)	-0.0109 (0.0261)	-0.00754 (0.0387)	0.00172 (0.0410)
Competition Index	-0.114 (0.0752)	-0.128 (0.0889)	-0.151 (0.181)	-0.232 (0.188)
Also Includes	Year	Year	Year	Year
	Interactions	Interactions	Interactions	Interactions
Observations	1,124	1,124	562	562
R-squared	0.958	0.959	0.958	0.960

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Efficiency

VARIABLES	(1) DEA Base FullSample	(2) DEA BaseBootstrap FullSample	(3) DEA Org FullSample	(4) DEA OrgBootstrap	(5) DEA Base DPSample	(6) DEA Org DPSample	(7) DEA Base DPOnly	(8) DEA Org DPOnly
Use EMR	-0.0332* (0.0196)	-0.0332*** (0.00940)	-0.0338* (0.0195)	-0.0338*** (0.0101)	-0.0314 (0.0197)	-0.0472* (0.0250)		
After EMR	0.0311** (0.0156)	0.0311*** (0.00889)	0.0247 (0.0151)	0.0247** (0.0109)	-0.00242 (0.0276)	-0.00373 (0.0365)	0.0335 (0.0508)	-0.0185 (0.0671)
ForProfit	0.0547*** (0.0156)	0.0547*** (0.00618)	0.0500*** (0.0154)	0.0500*** (0.00541)	0.0492*** (0.0109)	0.0353*** (0.0105)	0.308*** (0.0448)	
Union	-0.0288* (0.0150)	-0.0288*** (0.00877)	-0.0199 (0.0140)	-0.0199*** (0.00691)	-0.0178 (0.0134)	-0.0212* (0.0128)	0.0408 (0.105)	
Complaint Score	-0.000118 (0.000125)	-0.000118 (0.000119)	-0.000123 (0.000126)	-0.000123 (8.98e-05)	-0.000275** (0.000115)	-0.000306*** (0.000106)	3.41e-05 (0.000386)	-0.000206 (0.000358)
Deficiency Score	-0.000116 (0.000158)	-0.000116 (9.24e-05)	-0.000110 (0.000148)	-0.000110 (9.17e-05)	-0.000184* (0.000108)	-0.000159 (0.000100)	0.000151 (0.000604)	0.000526 (0.00100)
NYMetro	-0.0386* (0.0220)	-0.0386*** (0.00934)	-0.0406* (0.0223)	-0.0406*** (0.0113)	-0.0411*** (0.0119)	-0.0277** (0.0121)	-0.0218 (0.0236)	-0.00488 (0.0366)
Competition Index	0.190** (0.0955)	0.190*** (0.0616)	0.146* (0.0852)	0.146** (0.0658)	0.287*** (0.109)	0.0976 (0.104)	0.886** (0.336)	-0.209 (0.397)
Progressive			0.0154 (0.00987)	0.0154*** (0.00444)		0.0135*** (0.00518)		-0.137*** (0.0318)
EMR x Progressive			-0.0204 (0.0167)	-0.0204** (0.00936)		-0.134*** (0.0286)		
After EMRxProgressive			0.0174 (0.0133)	0.0174* (0.00919)		-0.0574** (0.0265)		-0.0633** (0.0232)
Year 2004	0.00604 (0.0115)	0.00604 (0.0120)	0.00225 (0.0117)	0.00225 (0.0142)	-0.0101 (0.0177)	-0.0175 (0.0169)	0.0542 (0.0636)	-0.0279 (0.0809)
Year 2005	0.00517 (0.00997)	0.00517 (0.0106)	0.00170 (0.00986)	0.00170 (0.0108)	-0.00853 (0.0176)	-0.0159 (0.0169)	0.0611 (0.0635)	-0.0335 (0.0811)
Year 2006	0.00662 (0.00900)	0.00662 (0.0131)	0.00580 (0.00891)	0.00580 (0.0106)	-0.00247 (0.0176)	-0.00310 (0.0169)	0.0301 (0.0638)	-0.0514 (0.0796)
Year 2007	-0.00494 (0.00722)	-0.00494 (0.00813)	-0.00199 (0.00746)	-0.00199 (0.0116)	-0.0121 (0.0172)	-0.0110 (0.0169)	0.00215 (0.0424)	-0.0288 (0.0605)
Year 2008	-0.0102* (0.00604)	-0.0102 (0.0118)	-0.00797 (0.00646)	-0.00797 (0.0116)	-0.0155 (0.0171)	-0.0139 (0.0167)	-0.0259 (0.0382)	-0.00684 (0.0440)
Observations	1,147	1,147	1,066	1,066	601	525	91	45
R-squared	0.125	0.125	0.124	0.124	0.102	0.124	0.486	0.591

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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